Currency Recognition System for Blind people using ORB Algorithm

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Abstract: *Despite the quickly expanding utilization of Master cards and other electronic types of payment, money is still broadly utilized for ordinary exchanges because of its convenience. However, the visually impaired people may suffer from knowing each currency paper apart. Currency Recognition Systems (CRS) can be used to help blind and visually impaired people who suffer from monetary transactions. In this paper, a Currency Recognition System based on Oriented FAST and rotated BRIEF (ORB) algorithm is proposed. The ORB is based on the FAST detector and the visual descriptor BRIEF (Binary Robust Independent Elementary Features). Its aim is to provide a fast and efficient alternative to Local Scale-Invariant Features (SIFT). The proposed system is applied to Egyptian paper currencies including six kinds of currency papers. Initially, some pre-processing operations are performed on a given currency paper input image. Then, important ROI is extracted from the background. The ORB Algorithm is used for a feature detection and description the input image. Finally, Hamming Distance is used for matching binary descriptors obtained from feature extraction stage. The proposed method is compared with another system (CRSFVI). The experimental results showed that the proposed system can be used in real-world scenarios to recognize unknown currency paper image with a higher accuracy of 96 % and a shorter running time of 0.682 s when compared with the CRSFVI system.*

Keywords: *Currency Recognition, FAST, BRIEF, Hamming distance, Illumination, ORB Algorithm.*

Received November 3, 2017; Accepted January 3, 2018

1. Introduction

Modern automation systems in real world require a system for currency recognition. It has various potential applications including banknote counting machines, money exchange machines, electronic banking, currency monitoring systems, assist blind persons etc. The recognition of currency is a very important need for Blind and visually impaired people. They are not being able to differentiate between currencies correctly. It is very easy for them to be cheated by the others. Therefore, there is an urgent need to design a system to recognize the value of currencies in an easy way regardless of rotation, illumination, scaling and other factors that may reduce the quality of the currency such as noisy, wrinkled and striped currencies [23].

World Health Organization estimated the number of visually impaired over the world is about 285 million people, 39 million of them are blind and the rest have low vision [9]. Many techniques for currency recognition were proposed. They focus on texture, color and sizes of notes currency paper. They are not efficient suitable techniques for visually impaired people. Most of these techniques are sensitive to illumination conditions and many of them relay on taking images at fixed environment setting such as: camera location and image background.

The computational power and camera availability of current smartphones make them a suitable candidate for currency recognition. However, a few work has tackled such problem. In this paper, a mobile system for currency recognition that can recognize the Egyptian currency in different perspective views and scales is proposed. Currency recognition in a changeable environment is a complicated problem because many uncontrolled conditions will influence the image quality. A smartphone application is developed to identify currencies that are partially visible, folded, wrinkled or even worn by usage [14]. The proposed system can recognize the Egyptian currencies of types (.5, 1, 5, 10, 20, 50, 100, 200 L.E.) and the result is translated to voice using sounds on the system that tell the value of the currency through the mobile speaker without people intervention. Figure 1 shows how the user of the system uses it to capture an image and get a result. Figure 2 shows Egyptian currencies from one-pound to two-hundred Egyptian pounds. Each row represents forward and back faces for every currency.

We used the ORB Algorithm to get the features of images as it is very fast algorithm regarding to the time. In addition, ORB is robust and efficient for getting binary descriptors. It relies on Oriented Fast and Rotated Brief Algorithm [1]. ORB is invariant to illumination, rotation and scaling. Many systems use ORB Algorithm like detecting moving objects in a moving background using ORB feature matching by camera [20]. In [23] the ORB is used in detecting a copy-move attacks that take a part of image and paste it in the same image for the purpose of hiding some information in digital images. It is also used in fuzzy-based automatic landmark recognition in Arial image auto-localization [16]. In addition to the previous work, there are a lot of researches used this Algorithm [7, 12 and 19].

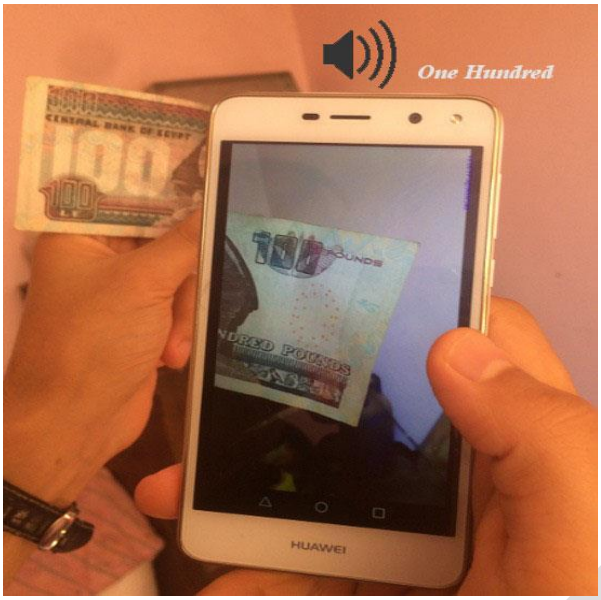

Figure 1. Demo of the system

Figure 2. Egyptian currencies.

1.1. Related Works

Many currency recognition systems have been proposed. In [6], the authors recognize and classify four different currencies using computer vision. The features are extracted based on texture, color and shapes of four different currencies. They use Artificial Neural Network for classification. The average Accuracy rate was 93.84%.

Iyad et al. developed a mobile currency recognition system using a dataset for Jordanian currencies [2]. They applied this method on a smartphone using the Jordanian dataset based on scale invariant feature transform (SIFT) algorithm [10]. The system produced accuracy 71% for paper currency and 25% for coin currency.

In [18], the author proposed a mobile paper currency recognition system that applied on Saudi Arabian papers. Recognizing paper currencies method is based on some interesting features and correlations between two images. It uses Radial Basis Function Network for classification. The system has an accuracy of recognition 95.37% for the Normal Non-Tilted Images, 91.65% for Noisy Non-Tilted Images and 87.5% Tilted Images.

Sungwook et al. proposed an efficient and fast algorithm for classifying multi national banknotes based on sizes information and correlation matching of multi templates [21]. As different banknotes have different sizes so this information was regarded to be important features. This method was tested using 55 currencies of 30 different classes from five countries: EUR, KRW, RUB, CNY, and USD. The results of this method achieved 100% classification accuracy for normal banknotes and 99.8% classification accuracy for defiled banknotes.

A non-parametric method is proposed in [3] for the identifying paper currencies. The proposed method is based on the development of a non-parametric model for each class of paper currency. The model is obtained by averaging all available samples of a one banknote. The tested banknote can be recognized by finding the coefficients values between the banknote and the non-parametric models and matching based on these values. For capturing the currency, the camera and currency should be aligned horizontally to get a good result. This method is applied to three kinds of Saudi Arabian banknotes and tested on wide range of currencies and the accuracy reaches to 100% of identification.

Noura et al. used a simple image processing operation to make a system for recognizing currencies CRSFVI [17]. This method uses the dataset that the proposed method used and the proposed method is compared with this method. Basic techniques applied in the proposed system include image segmentation, equalization, region of interests (ROI) extraction and then matching the template based on the correlations between the taken image and dataset on database. The results showed that this method can recognize Egyptian paper currencies with moderate accuracy reaches to 89% with 12 seconds running time.

Farid et al. introduced a recognition method for Mexican banknotes using artificial vision [4]. This method proved that the Mexican banknotes can be classified by extracting their texture features and color. This technique uses the RGB color model and the Local Binary Patterns for the identification process. the accuracy of this method is very low.

Junfang et al. used an improved LBP algorithm, called block LBP algorithm for characteristic extraction [5]. It is based on the ordinary Local Binary Pattern (LBP) method. This method is very simple and has a high speed. The experimental results showed that this improved method has a high recognition rate, as well as robust illumination changes and noise with an accuracy ratio from 92% to 98 %.

2. Proposed Method

Figure 3 shows the block diagram of the proposed system. We have two phases: (offline and online). the offline phase in which the dataset is constructed from a given collection of Egyptian currencies images. The online phase in which the proposed method is running in order to detect and recognize unknown input currency image. The online phase has five steps, preprocessing techniques for removing noises and preparing the image for next operations, segmentation and ROI extraction processes in the second and third step for extracting the foreground currency from background, applying ORB Algorithm in the step four and finally matching the results with the dataset. In the last step, the input to the system is obtained from the camera of any Android device and the output is a voice that inform the user with the value of the currency.

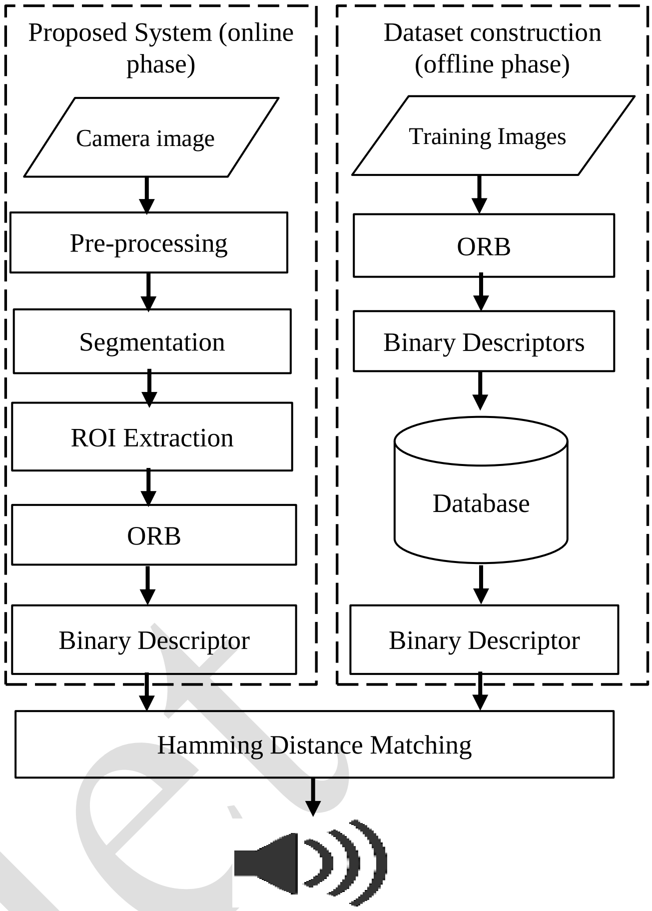

Figure 3. System block diagram.

2.1. Preprocessing

In this step, some image processing operations are performed to prepare the currency image for segmentation process. Gaussian blurring equation (1) is used to remove noise from the image and then sharpening the image help to segment the currency for the next step.

$$G(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (1)$$

Where x is the distance from the origin in the horizontal axis, y is the distance from the origin in the vertical axis and σ is the standard deviation of the Gaussian distribution [10].

2.2. Segmentation

The purpose of segmentation is to convert the currency image into binary image that consists of two colors black and white. Otsu Thresholding function is used to convert the RGB image to binary images of 0 and 1. 0 for black and 1 for white as shown in equation 2

$$T(x,y)=\begin{cases}1 & if\ T(x,y)\geq th\\ 0 & otherwise\end{cases} \quad (2)$$

Where *T* (x*, y)* is the density of the image and *th* is the threshold value that are adapted by the Otsu threshold technique [10].

2.3. ROI Extracting

To extract the currency from the image, the two-pass connected component Algorithm in [15] is used.

2.4. ORB Feature Extraction

2.4.1. ORB interest points and orientation

In this step, the oriented fast and rotated brief (ORB) Algorithm in [14] is used to perform the following operations for good performance:

- use the fast algorithm in [11] to detect corners and interest points in an image and adds the following features for better performance:
- Uses Harris corner detector in [22] to assign score for every interest point based on the variation of intensities around the corner point.
- Sorts the scored interest points and consider only N top corners.
- Compute the intensity-weighted centroid in [13] for interest points neighborhood.
- Computes the vector direction and assign it as the interest point orientation using the interest point and centroid.

2.5. ORB Description

After getting the interest points in the detector stage, we want to extract the feature description for these interest points, for this purpose, Brief algorithm in [1] is used to create the feature descriptors with respect to a local shape like rectangle or circle. The algorithm creates binary descriptors consisting of 0 and 1 binary numbers known as local binary descriptors. These binary descriptors are computed using the pixel pair sampling method where pair of pixels P1 and P2 is selected from 31×31 patch around every interest point as an example and compare them. If P1 is greater than P2 put 1 in the description vector as shown in the equation 3.

$$\tau\,(P{:}P1,\,P2) = \begin{cases} 1 & if\ P1 \geq P2 \\ 0 & otherwise \end{cases} \tag{3}$$

Where τ is the test of point 1 p1 and point 2 p2 and the result is 1 or 0 depending on the comparison of p1 and p2.

The process of ORB description is performed on the training set that are shown in Figure 5. The result of description is stored in the database then the same process is performed on the currency that is taken by the mobile camera and also store the description for the process of matching that are explained in the next step.

2.6. Matching

When blind user starts the mobile app. He has some seconds to capture the image. Then, the system applies the previous steps of pre-processing on the captured image. After that, ORB algorithm is applied to get the binary descriptors. Hamming Distance measure, in equation 4, is used to match with the previously stored descriptors in the database. It is very fast and efficient for matching binary texts.

$$D^{HAD}(i\ ,\ j) = \sum_{k=0}^{n-1} \left(Y_{i,k} \neq Y_{j,k}\right) \tag{4}$$

Where *D* is the Hamming distance between descriptors. *i* and *j*, and *k* are the indices of the respective variable *n*, *hamming* distance itself gives the number of mismatches between the variables paired by *k* [9].

After matching the descriptors, the greatest number of matches with the database informs that it matched with the currency with the same type as shown in Figure 4. The blind user can know the value of the currency by hearing from the speaker of the mobile phone a sound voice representing the matched currency value.

In Figure 4, the right image is the result of matching five pounds with the dataset. Number 47 indicates the maximum number of matching with database descriptors. The left image is the result of matching fifty pounds with the dataset.

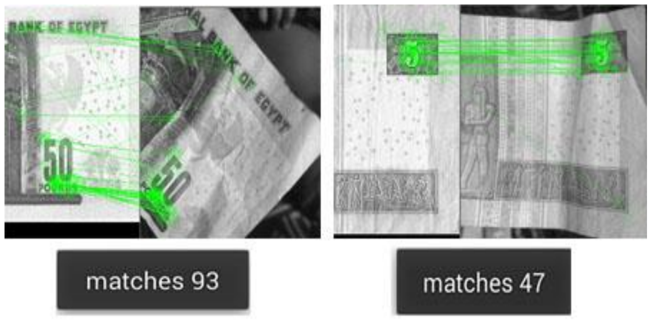

Figure 4. The process of matching using Hamming Distance.

Number 93 indicates the maximum number of matching with the all descriptors stored in the database so the final matching result is fifty pounds.

3. Results

In this section, we introduce the experiment procedure and images that are used as a training set and the results of the system.

3.1. Experiment procedure

The proposed system has been tested on many android devices. These phones are varying with the quality of the camera and properties. Results are very good in different environmental factors such as illumination, scaling, and rotation. The proposed system does not rely on a taking The image with a specified degree unlike the system introduced in [17] that require a pre-specified degree to get a good result.

The Mobile app needs to pre-configure for the first time of use. Anyone except the blind can do these configuration before the blind person can use the app. Firstly, download the voice access app to support voices to open applications in the mobile. Secondly, from settings, go to Accessibility and tab voice access then from the notification shade click on touch to start.

After making these configurations the blind can open the application by his voice by talking “what’s money” this the name of the application. Then, the app asks the blind to put the currency towards the camera as shown in Figure 1. The system will take some time to prepare its database for only the first time. Finally, the system will inform the blind the value of the currency by voice via the speaker of the mobile in less than one second

The proposed system is implemented using the libraries of OpenCV running on android platform. The OpenCV libraries are very useful and has a high speed in getting results. The proposed system gets the result in less than one second unlike the other systems in [2, 6] and [17] that take long time for testing. Figure 5 shows some of the training set of all Egyptian currencies of types (1, 5, 10, 20, 50, 100, 200 L.E.). As noticed from Figure 5, they do not represent the whole currency. They contain the important regions that have unique features to be stored later as features for every currency paper in the database. The whole currency is not stored in the dataset as there are many redundant features in different currencies so they may reduce the accuracy of the system and increase the time to get a result.

Figure 5. samples of training set used in the system.

In Figure 6, some test samples that are taken with different situations of scaling and illumination.

Figure 6. Test samples.

3.2. Visual Results

This section introduces some of different devices that have different properties of camera and RAM and also introduces the visual results on one of these devices. The proposed system is tested on different Android mobile phones like Samsung Galaxy Fame with camera resolution of 2 and 5 MB and 512 MB of RAM, Huawei Y5 with 8 MB camera resolution and 2 Giga memory RAM and another one of 5 MB Camera Resolution and 1Giga of RAM. Results showed that the proposed method is efficient and fast in all devices with very short time and high accuracy unlike other methods that use the same dataset and the same device.

The visual processes of the proposed system are shown in the figure 7 rows represent the test for one hundred, two hundred, five, and one hundred pounds back face respectively.

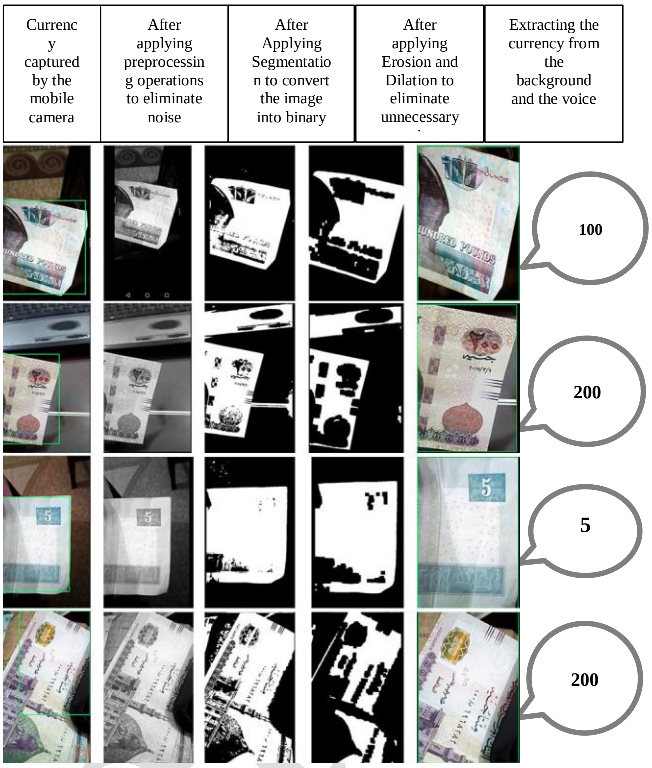

Figure 7. Visual test for some different Egyptian currencies.

3.3. System Evaluation

In this section, the accuracy of the proposed system is measured using the equation (5). The evaluation and comparison between the proposed method and CRSFVI regarding to time and percent of successful results.

$$Accuracy\ (\%) = \frac{\#succes\_tests}{\#success\_tests\ +\ \#failure\_tests} \times 100 \qquad (5)$$

Where #success_test is number of true results and #failure_tests is the number of false results as shown in Table 1.

In Figure 7 ,The 1st column represents the image that is captured by the mobile camera ,2nd column represents the that are required to convert the image into binary image of 1 and 0 , preprocessing operations that are required to eliminate noise , 3rd column represents the process of segmentation 4th column represents the process of Erosion and Dilation that are required to eliminate unnecessary regions from the image and the end column represents the process of extracting the currency from the background then this images is passed to ORB Algorithm to extract features and matching, these features with the database, then the value of the currency is informed to the blind via mobile phone speaker.

Table 1 shows the accuracy between the proposed algorithm and CRSFVI system in [17]. The total number of currencies used to compare them is 185 currency papers distributed on different kinds of currencies as illustrated from second column in Table 1. The accuracy for the proposed system proved that it achieved a high accuracy unlike CRSFVI system in accuracy and time.

Table 1. Accuracy of the proposed system and CRSFVI.

currency	# of samples used for each currency		# of success currencies each Alg. detects		# of failure currencies each Alg. detects		Accuracy %	
	CRSFVI System	Proposed System	CRSFVI System	Proposed System	CRSFVI System	Proposed System	CRSFVI System	Proposed System
1 pound	-	25	-	23	-	2	-	92
5 pounds	20	30	18	29	2	1	90	96
10 pounds	20	30	17	28	3	2	85	94
20 pounds	20	30	20	30	0	0	100	100
50 pounds	20	25	16	24	4	1	80	96
100pounds	20	25	17	24	3	1	95	96
200pounds	20	20	19	20	1	0	85	100

As shown in table 2, the proposed method achieved a very fast time for processing the input image and get the result unlike the other method and the overall accuracy for proposed system is 96% while the CRSFVI system accuracy is 89%.

Table 2. Runtime and average Accuracy between proposed and related method.

Method	Proposed method	CRSFVI
Runtime/seconds	0.682	12
Overall Accuracy	96%	89%

4. Conclusion

In this paper, a mobile based currency recognition system for blind and visually impaired using ORB Algorithm is proposed. This method applied some image processing operations to remove the noise. Then, ROI is extracted by using the connected component Algorithm. The ORB is applied to get the binary descriptors to be stored in the database. Finally, matching the results with the descriptors in the database using hamming distance technique. The evaluation results show that the proposed system outperforms the CRSFVI system in terms of processing time and accuracy. In the future work, we will add other currencies of different countries and improve the method by using other matching techniques to improve the accuracy to get 100 % of results.

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